Integrated Guidance and Control of AUVs Using Shrinking Horizon Model Predictive Control

Charmane V. Caldwell[1], Emmanuel G. Collins[2], and Srinivas Palanki[3]

Center for Intelligent System, Control and Robotics
[1]Department of Electrical and Computer Engineering, [2]Department of Mechanical Engineering,
[3]Department of Chemical and Biomedical Engineering,
Florida A&M University-Florida State University College of Engineering,
2525 Pottsdamer St., Tallahassee, Florida 32310-6046

Abstract- **There are problems controlling autonomous underwater vehicles (AUVs) because they are nonlinear and coupled and have external environmental disturbances acting on the vehicle. More difficulties arise when the vehicle tasks require precise positioning and control as in military missions. This paper presents an integrated guidance and control method for an AUV. The algorithm is based on an optimal control method called shrinking horizon model predictive control (SHMPC). Scenarios for reconnaissance and reacquisition in mine countermeasures missions are explored applying SHMPC. In addition, there are scenarios with obstacle avoidance. Simulations of this method show the control method is able to systematically handle disturbances and constraints to successfully maneuver through volatile areas.**

I. INTRODUCTION

There are various Autonomous Underwater Vehicles (AUVs) around the world, ranging from the Odyssey II to the REMUS vehicle, with each vehicle performing different tasks. Some AUV applications are cable/pipeline inspection, sea floor mapping, oil exploration, geological sampling, deep-sea exploration, environmental monitoring, underwater rescue, wreckage recovery and military missions. In recent years with the introduction of littoral warfare the Navy has been driven to make an investment in mine countermeasures (MCM).

In the latest Iraq war, REMUS AUVs were employed in the Arabian Gulf to aid in the detection and clearing of mines [4]. As part of the Naval Special Clearance Team-One (NSCT-1) which consisted of Navy Seal divers, Explosive Ordinance Disposal (EOD) divers, Marine Corps forces and dolphins, the Navy used the REMUS specifically for searching the area for mine-like objects. It was believed that using the AUVs in this limited role decreased the mission by two days. Even though the Navy has had the Remus since the late 1990s, this marked the first time AUVs had been used during wartime. The Navy's goal is to increase the intelligence of the vehicle to eventually be able to decrease soldier intervention in this dangerous process. Special emphasis is placed on the surf zone (SZ) and very shallow water (VSW) (40 feet or less) where soldiers are most susceptible. The AUVs ability to complete the mission without being detected is a plus. In addition, AUVs are attractive because there are significant logistical advantages because of its small size and the reduced monetary cost of the operation.

The procedure for MCM missions depend on the situation at hand. There are several subtasks that usually take place, including search, detect, classify, identify, and neutralize/avoid. In the first stage of a MCM mission, the AUVs search unsecured areas for mine-like objects. The time allowed to investigate the area is limited due to both military concerns and battery life. Upon detection of a mine-like object, it is necessary to determine whether the object is actually a mine. Therefore, the AUV must carefully examine the recorded area at a standoff distance that is far enough away as not to cause the mine to activate, yet close enough that the object can be identified by a camera or other sensor. Those objects identified as mines can be neutralized or just avoided entirely. If the mine is to be neutralized, there is the added challenge of reaching the target with precision. Hence, a robust controller is required that is not sensitive to uncertainties that arise due to noise or disturbances.

There are several problems in general when attempting to control AUVs. The major concern when trying to control the vehicle is that they tend to have nonlinear and time-variant dynamics that are greatly coupled. There are also uncertainties in the hydrodynamic coefficients, which effect the confidence in the dynamic model. The vehicle is underdamped and easily perturbed which is a challenge when there are external disturbances like ocean currents that cause the vehicle to deviate from its path. Furthermore, the center of gravity and buoyancy may change depending on the payload. A variety of control schemes have been proposed for AUV control. A detailed review of the history of unmanned underwater vehicles (UUVs) control can be found in Craven (1998) and Fossen (2002).

This paper suggests the use of Model Predictive Control (MPC) because it naturally handles multi-input multi-output (MIMO) control problems, while systematically handling constraints during the design process; thus it allows the system to operate closer to constraints compared to conventional control methods. There are several researchers who have simulated or implemented some form of MPC on UUVs in recent years. Oh and Oh (2002) proposed utilizing MPC for

the homing and docking of an AUV. A separate controller was implemented for each application. Lisboa et al. (1997) have used MPC with a Neural Network model to control the depth of an Underwater Robotic Vehicle (URV) for the purpose of hovering. Sutton and Bitmead (1998) simulated MPC on an unmanned submarine with an objective of keeping the vehicle 50m above the sea floor with movement only in the X-Z plane. Kalebi et al. (1999) suggest a three layer AUV control architecture where MPC is the middle layer for guidance and H_∞ control is used in the bottom layer to control the actuators.

There has been research done on implementing MPC on AUV hardware. Miotto et al. (2003) use D* to replan the path in case of obstacles, then B-Spline to smooth the generated lines to give the reference trajectory (guidance). MPC is then implemented between the guidance layer and autopilot to provide the control command for the *Manta* test vehicle. Naeem et al. (2005) make use of a Line of Sight (LOS) technique to generate the reference trajectory. MPC is employed in determining the control input needed to keep sufficient heading for following the trajectory. This technique is implemented in real time on *Hammerhead* utilizing a genetic algorithm for optimization.

Other than Katebi et al. (1999), the previous methods use MPC to find the control effort necessary to follow a predetermined trajectory. In contrast, this research utilizes shrinking horizon model predictive control (SHMPC) to determine the optimal path and find the control effort simultaneously. This research goes one step further than those listed above. Unlike most of the other methods that linearize the model, a nonlinear kinematic model is used. In addition, this research controls a multi-input multi-output model where some of the previous researchers only explored controlling the depth or heading separately. Other than Miotto et al. (2003), the prior mentioned research assumed an ideal situation of a clear area with no obstacles. In contrast, this research deals with obstacles, which yield additional constraints for the optimization problem.

This paper is arranged in the following manner. Section 2 briefly reviews MPC and lays out the differences between receding horizon model predictive control and SHMPC. It also shows the benefits and downfalls of using MPC. Lastly, it demonstrates how obstacle avoidance can be incorporated into the constraints. Section 3 first describes the model employed for the simulation results. Then, scenarios are shown where a search of the area and reacquisition of an object are performed. It also illustrates how the vehicle behaves when obstacles are put in its path. Finally, Section 4 presents conclusions and describes ongoing research.

II. MODEL PREDICTIVE CONTROL

This paper considers the application of MPC to the MIMO nonlinear plant,

$$\begin{aligned} x(k+1) &= f\big(x(k), u(k), w(k)\big) \\ y^m(k) &= g\big(x(k)\big) + \xi(k) \end{aligned} \tag{1}$$

where $x(k)$ is the states, $u(k)$ is the input, $w(k)$ is the unmeasured disturbance, $y^m(k)$ is the measured output and $\xi(k)$ is the measurement noise. Introduced to the process industry in the late 1970's, MPC is a mixture of system theory and optimization. It is a control method that finds the control input by optimizing a cost function subject to constraints. The cost function calculates the desired control signal by using a model of the plant to predict future plant outputs. There are several versions of MPC, but they can all be thought of as either receding or reducing horizon.

A. Receding Horizon Model Predictive Control

MPC has three stages: Prediction, Optimization and Control. Fig. 1 provides a diagram of the stages used in MPC. At every time step k the future plant output is predicted for a pre-determined N steps ahead (called the prediction horizon). The predicted outputs are a function of past inputs and outputs in conjunction with future control inputs. A fundamental part of this method is the actual optimization problem that obtains future control inputs by minimizing a cost function subject to constraints on the system. Typically, the cost function J consists of the error between the reference trajectory r and the predicted outputs y in addition to the control effort u. In particular, the optimization problem is

$$\min_u J = \sum_{i=1}^{N} \left\| r(k+i) - y(k+i) \right\|_Q^2 + \sum_{i=0}^{M-1} \left\| \Delta u(k+i) \right\|_S^2 \tag{2}$$

subject to the model constraints,

$$\begin{aligned} x(k+i) &= f\big(x(k+i-1), u(k+i-1)\big) \\ y(k+i) &= g\big(x(k+i)\big) + \beta(k) \end{aligned} \tag{3}$$

and the inequality constraints,

$$\begin{aligned} &Ax \le b \\ &C(x) \le 0 \\ &u^l \le u(k+i) \le u^u \end{aligned} \tag{4}$$

where the prediction and control horizons are N and M respectively, $\beta(k)$ is a bias expression that compares the current predicted output $y(k)$ to the current measured output $y^m(k)$, $C(x)$ represents the nonlinear constraints on the states, and Q and S are respectively the error and control effort weights.

Only the first optimal control input is implemented on the plant. Then the process starts over. This method is commonly referred to as receding horizon MPC because the prediction window is constantly moving. The objective is to get the predicted output $y(k+i)$, $i = 1, \cdots N$ to reach the reference tra-

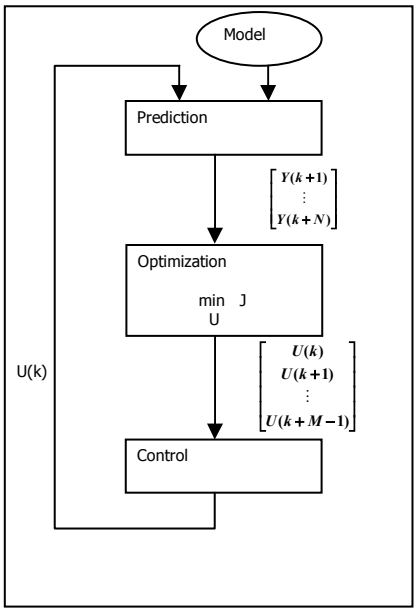

Figure 1. Stages of MPC algorithm.

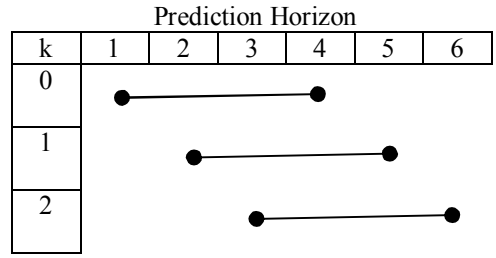

Figure 2. Concept of Receding Horizon Model Predictive Control

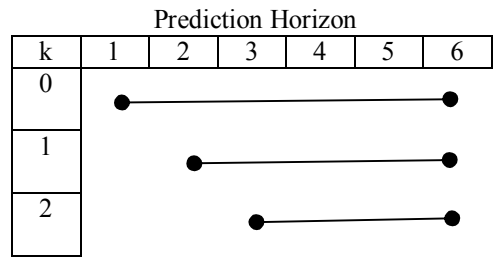

Figure 3. Concept of Shrinking Horizon Model Predictive Control

jectory $r(k+i)$ utilizing the proposed inputs $u(k+i)$ during the prediction horizon N. To acquire a better understanding of the receding horizon concept refer to Fig. 2. Here the prediction horizon, $N=3$, is fixed and moves by one sampling interval at each step. This is also sometimes called the moving horizon.

B. *Shrinking Horizon Model Predictive Control*

For the AUV applications considered in this research, it is necessary to consider a second method of MPC called Shrinking Horizon Model Predictive Control (SHMPC). Here, as illustrated in Fig. 3, the horizon of the model prediction decreases as time increases. The horizon window is not fixed; it decreases by one sampling interval at each step. Hence, the horizon "shrinks" as the end of the mission approaches. In this method, instead of having a pre-determined reference trajectory to attempt to follow, there is a target point that the control variables or outputs must reach in a fixed amount of time, yielding the optimization problem,

$$\min_{u} J = \sum_{i=1}^{N^*-k} \left\| G - y(k+i) \right\|_Q^2 + \sum_{i=0}^{M-1} \left\| u(k+i) \right\|_S^2 \qquad (5)$$

subject to (3) and (4), where G is the constant output goal and N^* is the endpoint. The first term in the cost function represents the deviation of the predicted output from the set point G. The prediction window is decreased by 1 as the time step is increased by 1. This allows the endpoint values to be incorporated since there is only an interest in reaching the setpoint at the end of the mission. Here, the optimizer computes a sequence of control inputs for each step up to the endpoint. In other words, SHMPC executes end-point optimization. It is able to regulate the control inputs to optimize the output values at the final step. In this method the trajectory and necessary control inputs needed to reach the desired end-point are calculated simultaneously. The decisions SHMPC makes during this progression have a considerable effect on the final output.

C. *Benefits of MPC*

MPC has several benefits that make it attractive for use on AUVs. It naturally handles MIMO control problems so it can lead to better control of AUVs than classical control methods. Constraints can be systematically included during the design process, unlike conventional control methods, so physical limitations of the vehicle can be addressed. MPC can control systems with long delay times, non-minimum phase systems or unstable systems. This method creates a control that compensates for the dynamics of the plant. MPC has a look ahead feature that enables the compensation of future errors, whereas a conventional control method like PID can only compensate for an error once it has occurred. Using MPC enables the vehicle to take into account disturbances and possible constraint violations and intelligently re-examine its status. It performs this re-examination at every time step and only implements the first control input, making this method robust. One of the most important features of MPC is that the shrinking horizon control method provides the ability to compute the trajectory.

D. *Weaknesses of MPC*

This discussion would not be complete without considering weaknesses of this method. MPC tuning procedures are not as clearly defined as in classical control methods. This shortcoming is because the relationship between tuning parameters and closed loop behavior is not explicit. Another problem is that an optimal solution may not be found, depending on the time available to compute a solution. Hence,

TABLE I

SIMULATION CONSTRAINTS

Parameter	Min	Max
u	0 (m/s)	2.8 m/s
p	-π/6 (rad/s)	π/6 (rad/s)
q	- π/6 (rad/s)	π/6 (rad/s)
r	- π/6 (rad/s)	π/6 (rad/s)
ϕ	-π	π
θ	- π /2	π /2
ψ	-2 π	2 π

only a sub-optimal solution may be obtained in certain cases.

E. *Obstacle Avoidance*

As discussed earlier, MPC allows the controller to systematically handle constraints. Equation (4) shows the constraints the cost function is subject to. Hence, avoidance of an ellipsoid obstacle can be modeled as a nonlinear constraint:

$$(X\text{-}O_x)^2 + (Y\text{-}O_y)^2 \geq R^2 \tag{6}$$

where X and Y are the vehicles x and y position, respectively. The obstacles center location is at (O_x, O_y) with a radius of R. In order to formulate the obstacles this way, we assume that the objects are stationary and that the position is known ahead of time.

III. SIMULATION RESULTS

The simulations for this paper considered the REMUS AUV kinematic model in the SHMPC algorithm. As such all the results have constraints on the forward velocity, body velocity and orientation as detailed in Table 1.

A. *Kinematic Model*

An AUV model approximates the vehicle's movement as a response to specified inputs. The kinematic model is a simple mathematical model that does not take into account the forces acting on the vehicle. The AUV posture can be defined by six coordinates, three representing the position (x, y, z) and three corresponding to the orientation (φ, θ, ψ), all with respect to the world frame. The model plainly demonstrates how the body frame's linear and angular velocities relate to the world frame velocities. To simplify the model, the velocity along the y and z axes are neglected to produce:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} \cos\theta\cos\psi \\ \cos\theta\sin\psi \\ \sin\theta \end{bmatrix} [u] \tag{7}$$

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi\sec\theta & \cos\phi\sec\theta \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{8}$$

where u is the linear velocity along the x axis and p, q, r are the angular velocities along the x, y, z axes, respectively. Consequently, there are four inputs and six states in this model.

B. *Reconnaissance*

The prediction horizon $N^*=15$ and control horizon $M=1$ are kept constant throughout the simulation. The program was written in MATLAB using the function FMINCON for the optimization stage. Fig. 4 represents the scenario of the vehicle being given several waypoints to visit in order to search an area. It is similar to a mow-the-lawn pattern. However, the movement is not forced. Since the model is included in its decision making, its commanded movement is kinematically feasible as it moves from one waypoint to the next waypoint, such that the vehicle does not have an instantaneous change of direction. Fig. 5 shows the results when an input disturbance (such as a current) of -1 m/s is introduced. The disturbance causes the vehicle to struggle to

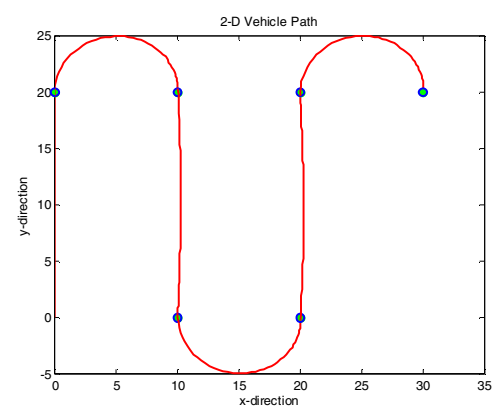

Figure 4. Search of area without input disturbance.

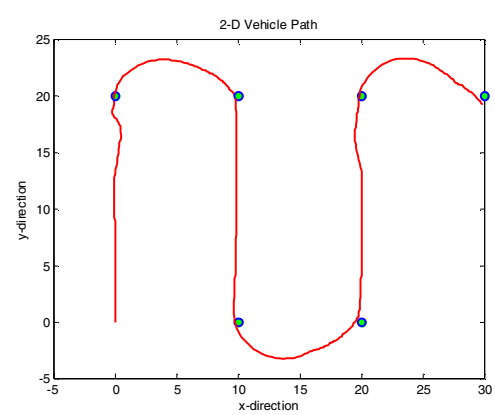

Figure 5. Search of area with input disturbance.

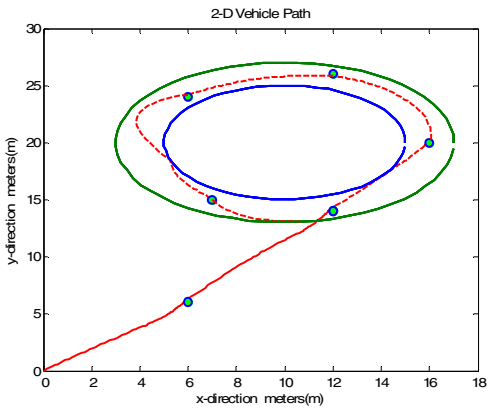

Figure 6. Reacquisition of object.

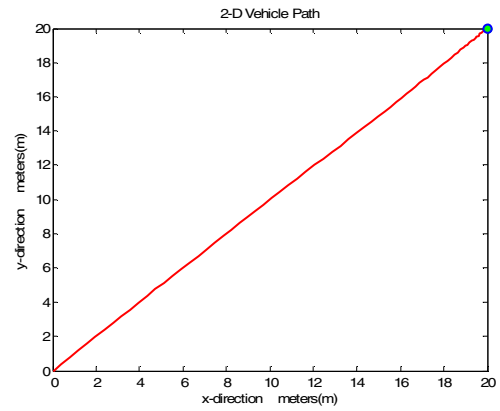

Figure 7. Movement from a start position to a goal position with no obstacles.

get to the waypoint. However, the controller is capable of handling it and reaches each of its waypoints. Note that in all of these cases, the trajectory is not pre-determined. The algorithm calculates the trajectory in the process of reaching the next waypoint.

C. Reacquisition

The plot in Fig. 6 emulates a case were a reacquisition is required for an object with a previously recorded position. The AUV has to approach the area where the target is expected to be located. The vehicle has to circle the object. The vehicle in this situation is given an added constraint of staying within set circular regions around the object. As stated before, the vehicle needs to keep a safe distance away depicted by the (inner circle) yet close enough (outer circle) to be able to identify the object as mine-like. At certain times the vehicle will come close to the constraint; however, the AUV never violates the constraint once it gets inside the region.

D. Obstacle Avoidance

In each of these cases, there are 7 obstacles in the area that the vehicle must maneuver around in order the reach the target. By modeling the avoidance of each obstacle as in (6), it is possible to achieve a successful mission. In the first scenario in Fig. 8, the vehicle has a start posture of ($0m$, $0m$, 45°) and a goal posture of ($20m$, $20m$, 45°). There are objects at random locations in the area. If the objects were not there, then the AUV would have just moved in a straight line as in Fig. 7. However because of the objects centered at ($8m$, $8m$) and ($12m$, $12m$) an alternative route had to be established. The vehicle actually begins in the original direction of Fig. 7, but changes its direction in order to successfully traverse through the area. The second scenario is used to truly demonstrate MPC look ahead capabilities. In some path planning methods there are cases were the vehicle will hit a local minimum and have trouble attempting to get around a wall where the goal is on the other side. Fig. 9 shows that because the vehicle considers the control that is needed to reach the endpoint along with the constraints in a systematic way it is able to avoid the wall altogether to reach the goal.

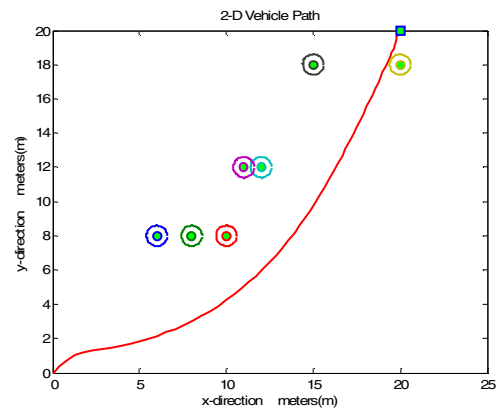

Figure 8. Movement from a start position to a goal position with obstacles.

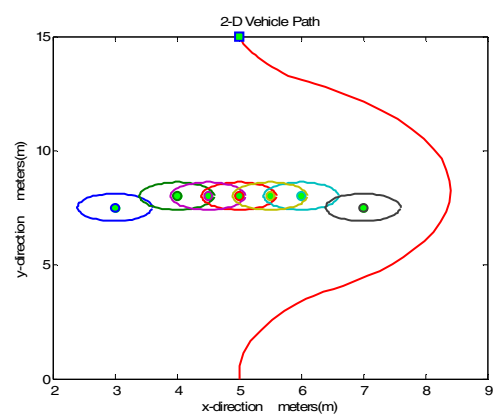

Figure 9. Maneuver around wall of obstacles.

IV. CONCLUSION

A novel approach to integrating the guidance and control of an AUV using SHMPC has been established. The control algorithm exploits end point optimization to achieve this. This paper proposes this method as a good controller for MCM missions. This method is able to accomplish maneuvering around obstacles in a systematic way and compensate for in-

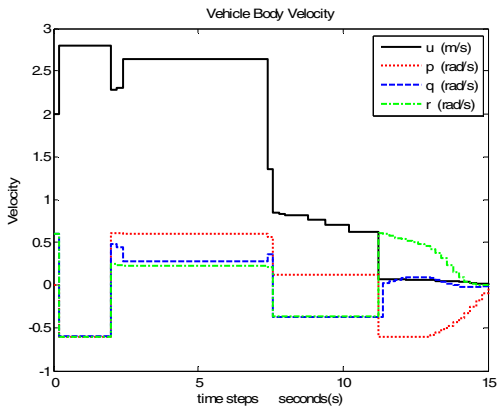

Figure 10. Inputs for maneuver around wall.

put disturbances. SHMPC meets the goal of accomplishing a more intelligent vehicle, since the AUV is able to determine its own trajectory.

There were some limitations in this research. The computation time needed to optimize at each time step would not allow the vehicle to operate in real time. Also the optimization method that was used was not robust. Various paths would be generated depending on the initial parameters given to the function FMINCON.

These were only preliminary results. Future goals of this research are to consider additional performance criteria such as time and battery life. In addition, it will attempt to address the real time problem and apply another optimization method such as a genetic algorithm or swarming.

ACKNOWLEDGMENT

C.V.C would like to acknowledge support from the Office of Naval Research Historically Black Engineering College/University (HBECU) Future Faculty Fellowship. Also to thank the staff of the Laboratory of Autonomous Intelligent Robots (LAIR) at Naval Surface Warfare Center – Panama City (NSWC-PC).

REFERENCES

[1] Craven P.J., Sutton R. and Burns R. S., "Control Strategies for Unmanned Underwater Vehicles," *The Journal of Navigation*, vol. 51, 1998, pp. 79-105.

[2] Katebi M.R. and Grimble M.J., "Integrated control, guidance and diagnosis for reconfigurable autonomous underwater vehicle control," *International Journal of Systems Science*, vol. 30, no. 9,1999, pp. 1021-1032.

[3] Fossen, Thor I., *Marine control systems: guidance, navigation and control of ships, rigs and underwater vehicles*, Marine Cybernetics, 2002.

[4] Jordan K. "Remus AUV Plays Key Role in Iraq War," *Underwater Magazine*, July/August 2003.

[5] Liotta, V., Georgias, C., El-Aasser M., "Real-Time Estimation and Control of Particle Size in Semi-Batch Emulsion Polymerzation," *Proceeding of American Control Conference*, Albuquerque, New Mexico, pp. 1172-1176, June 1997.

[6] Lisboa P.J.G., Kodogiannis V.S., Lucas J., "Neural network identification and control of an underwater vehicle," *Transactions of the Institute of Measurement and Control*, vol. 19, no. 4, pp. 202-210,1997.

[7] Maciejowski J.M., *Predictive Control: with Constraints*, Prentice Hall, Haslow, UK, 2002.

[8] Miotto P., Wilde J. and Menozzi A., "UUV On-Board Path Planning in a Dynamic Environment for the Manta Test Vehicle," *Proceedings OCEANS 2003*, vol 5, pp. 2454-2461, September 22-26, 2003.

[9] Naeem W., Sutton R., Chudley J., Dalgleish R. and Tetlow S., "An online genetic algorithm based model predictive control autopilot design with experimental verifications," *International Journal of Control*, vol. 78, no. 4,pp. 1076-1090, 2005.

[10] Oh M.H. and Oh J.H., "Homing and Docking Control of AUV using Model Predictive Control," *The Proceedings of the Fifth ISCPE Pacific/Asia Offshore Mechanics Symposium*, Daejean, Korea, pp. 130-142, Nov. 17-20, 2002.

[11] Qin S.J. and Badgwell, "An overview of nonlinear model predictive control applications," in *Nonlinear Predictive Control*, Eds F. Allgoewer and A. Zheng, Birkhauser, 2000.

[12] Sutton G. J. and Bitmead R.R., "Experiences with Model Predictive Control applied to a Nonlinear Constrained Submarine,",*Proceeding of IEEE CDC*, Tampa Florida, December 1998, pp. 1370-1375.

[13] Thomas M.M., Kardos J.L. and Joseph B, "Shrinking Horizon Model Predictive Control Applied to Autoclave Curing of Composite Laminate Materials," *Proceeding of the American Control Conference*, Baltimore MD, pp. 505-509, June 1994.

[14] Von Alt, C., Allen, B., Austin, T., Forrester, N., Godsborough, R., Purcell, M., Stokey, P, "Hunting for Mines with REMUS: A High Performance, Affordable, Free Swimming Underwater Robot," *Proceedings of OCEANS 2001*, Honolulu, HI, pp. 117-122.

[15] Xiong Z., Zhang J., Wang X. and Xu Y., "An Integrated Batch-to-batch Iterative Learning Control and within Batch Control Strategy for Batch Processes," *Proceedings of the American Control Conference*, Portland, OR, pp. 1935-1940, June 2005.

[16] *Unmanned Vehicles for Mine Countermeasures*, http://www.onr.navy.mil/nrac/docs/2000_es_unmanned_vehicles_mine_countermeasures.pdf, Nov 2000.